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DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

Referring to Fig. 1, an engine such as a gas turbine engine used in aircraft is shown schematically by dash-line 11. A model is constructed having a gas path model 15, a lube oil model 17 and any other subsystem models 19 that may be selected for the monitoring of the engine.

The gas path model 15 is shown in Fig. 2 in detail, where external inputs 21, including customer bleeds, shaft power load, and starter torque are sent from sensors (in external inputs 21) to a CMEM model 23, which is a Component Map-based Engine Model and it is a nonlinear model. The incoming engine data is stored and processed. Ambient operating inputs 25 including, for example, temperature, pressure, Mach number and speed. Engine control unit inputs 27 are input into CMEM 23, including fuel commands and surge bleed valve control elements. Residuals are calculated by comparing the actual data inputs (on a continuous or steady state basis) with model predicted values that model CMEM 23 has determined for a set of data that represents the operating conditions of the engine being monitored. Model outputs 29 are computed for all the operating conditions, including shaft speeds, all temperatures, all pressures and all air flows.

Similarly, the Lube System Thermal Model 31 shown in Fig. 3 receives data in from External Inputs 33, including shaft power load and fault input defined as percent clogging of the air and oil cooler. Ambient Operating Inputs 35 include temperature, pressure and altitude, which the Lube System Thermal Model 31 processes to provide Model Outputs 37 to give Lube Oil Temperatures and all air flows.

A number of engines were evaluated in the field with the present invention and relevant sensor readings have been compared. EGT (exhaust gas temperature), N2 (engine speed), LOT (low oil temperature), HOT (high oil temperature) and fuel flow are compared and the percent error is calculated. Percent error is defined as the Model data value minus the sensor data value times 100 and divided by the sensor data value. [(model-

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(e.g., 2% degradation of turbine) are easy enough to detect using the method of this invention.

TABLE I
Typical Fault Signatures (1% change)

HP Turbine	Bleed Band	Lube System
N2 -0.6%	N2 +0.3%	HOT +0.6%
Fuel Flow +0.6%	Fuel Flow + 0.7%	LOT + 0.5%
EGT + 12 °F	EGT + 9 °F	
P3 - 0.5%	P3 - 0.3%	

Anomalies are detected using analysis of residuals. When residual errors exceed statistical control limits calculated from normal operations, there is a probability that the system is behaving abnormally. For example, Fig. 6 shows anomaly detection for the lube oil system using HOT and LOT residuals. An anomaly is detected when the residuals exceed desired confidence bounds. In this case it is observed that the possibility of abnormal system behavior exists between sample numbers 100 and 150 for both HOT and LOT residuals. After sample number 150 the lube system was repaired and the residuals returned to normal levels within the control limits. The dashed line shows the 99.3% confidence (5-sigma) bound and the dotted line shows the 95.5% confidence bound. Using the higher degree of confidence 99.3% bound reduced false positives in anomaly detection. In this case we can be fairly certain (>99.3%) that there was an abnormal event when values of both HOT and LOT residuals are consistently higher than the 99.3% bound between sample numbers 100 and 150.

A systematic method is used to detect faults using fault models. A fault is validated using one or more signatures after an anomaly is detected. For diagnosis, the dataset is analyzed at a specific time for a fault. The approach is similar to pattern matching. Using the fault model, a search on the fault intensity parameter is made such that the error residuals return within their respective control limits.